AJAE appendix for COVID-19 and Supply Chain Disruption: Evidence from Food Markets in India

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Note: The material contained herein is supplementary to the article named in the title and published in the American Journal of Agricultural Economics.

Online Appendix

A Online Data

The online data is scraped on a daily basis and once a day for every city. The products that are not available are counted as out of stock for the entire day for that city. Since each city is scraped at a similar time each day and our main estimates are based on within city comparison, the variability in product availability due to time of scraping does not affect our results. Additionally, we show that our scraped online prices capture the general price trends in urban India very well. We construct an online price index using the official weight of commodities in the Consumer Price Index (CPI) basket. This is shown in Figure A.1.[1]

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The index covers forty-two percent of the urban CPI basket (thirty-six percent food and six percent fuel). The index uses the same weights as those in the CPI basket to arrive at the final index price. In Figure A.1, the online index is reported from January 1, 2018 - December 31, 2019 by black line. The red dots correspond to the official urban price index value reported by the Ministry of Consumer Affairs.[2] We can see that the online price index tracks the urban prices in India well. Furthermore, it is also able to track the changes in the direction of prices at the peaks and troughs of the cycle. Overall, it shows that the online market is not disconnected from the offline retail market for the food commodities used in our paper.

We also report the price stickiness for the set of products used in our main analysis in Table A.1. The prices are least sticky for fruits and vegetables and change on an average every 9.1 days. Also, when the prices change, the absolute size of median change is around 14.2 percent. It goes in line with high volatility in food price inflation in India. The other non-perishable products are more sticky and take longer to change and the median absolute size of change is also lower. The stickiness for food products is lower and has been reported in earlier work by Cavallo 2018.

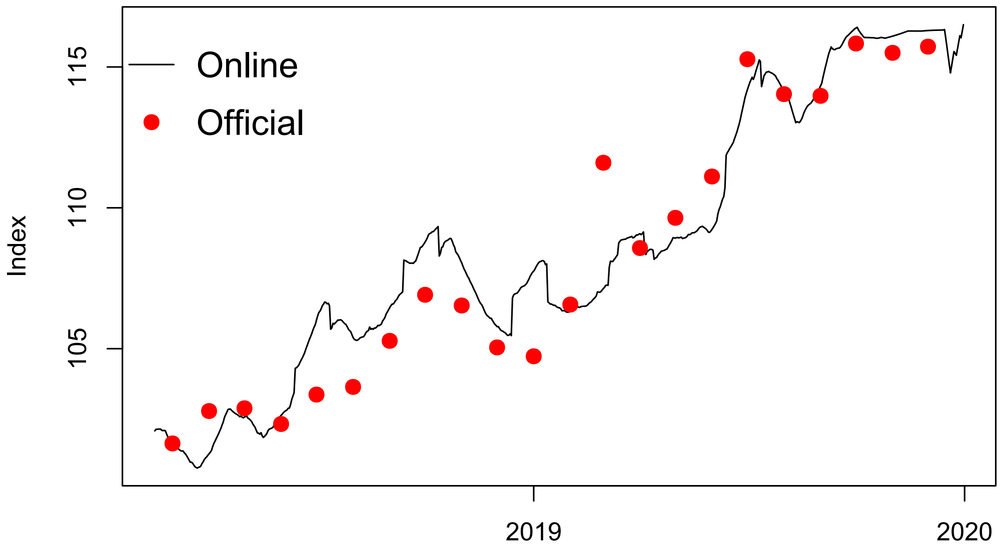

Figure A.1: Online vs Official price index

Notes: The figure gives a comparison of online vs official price index (urban) for a subset of commodities in the official CPI basket of India. The online index is constructed based on food and fuel items and has a weight of around forty-two percent in the urban CPI basket.

Table A.1: Price Stickiness in Online Data

Variable	Veggies & Fruits (1)	Cereals (2)	Pulses (3)	Edible Oils (4)
Average Days for Change	9.1	25.0	15.6	25.8
Median (Absolute) Size Change (%)	14.2	7.4	6.4	4.9

Notes: The above statistics are based on prices data from 2019 for the three cities and the same set of products used in the main analysis. The Average Days for Change gives the average number of days it takes for price to update at the product level. The Median (Absolute) Size Change (%) is the median over absolute size of price change, when the change happens. We drop the missing values in our computation.

B Offline Data for Prices

In this section, we estimate the impact of the lockdown on prices using offline retail price data. This data is collected by the Department of Consumer Affairs (DCA) for 22 essential commodities across major cities of India. We use the data for the three cities included in our analyses. We divide the 22 commodities into four subsets that correspond to the main categories in our paper. The vegetables and fruits include potato, onion and tomato (POT). The DCA data thus covers very few commodities under vegetables and fruits. The edible oils include mustard oil, sunflower oil, soyabean oil, palm oil, groundnut oil, and butter. The pulses include all the major pulses (gram, masoor, moong, tur and urad), while cereals include rice and wheat.

As in the baseline specification, we restrict our sample to the same dates before and after the lockdown. Finally, it is important to mention that the prices collected by DCA are at the commodity level and do not allow one to control for product level heterogeneity. We thus use a modified form of the estimation equation as given below:

$$ln(P_{ic,t}) = \beta_0 + \beta_1 * Lockdown_t + \delta_{ic} + \delta_{dow,c} + \varepsilon_{ic,t}$$

where $ln(P_{ic,t})$ is the log price of commodity i in city c on date t. The indicator variable $Lockdown_t$, is equal to one if India was under the national lockdown on date t, else it is zero. We also control for non time-varying heterogeneity at the commodity-city level through the fixed effects δ_{ic}. Table B.1 report the estimates. The results show that the lockdown led to a small increase in prices (less than 6 percent) for all commodities except for POT. The magnitude of the increase in DCA retail prices is similar to the online change in price for cereals and pulses. Since, the exact product of the commodity sold is not provided in the DCA data, one cannot know if the change in price is due to a change in the product mix. This could lead to some divergence in price trends across online and offline datasets.

Table B.1: Impact of Lockdown on Retail Prices (Offline)

Variable	Veggies & Fruits (POT)	Edible Oils	Cereals	Pulses
	(1)	(2)	(3)	(4)
Lockdown	0.160***	0.026***	0.026***	0.054***
	(0.012)	(0.003)	(0.003)	(0.003)
R-Sq	0.833	0.975	0.984	0.964
Observations	390	687	345	645
City×Commodity FE	Y	Y	Y	Y
City×Day of Week FE	Y	Y	Y	Y

Notes: The dependent variable is log price of the product. POT includes Potato, Onion and Tomato. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

C Figures and Tables

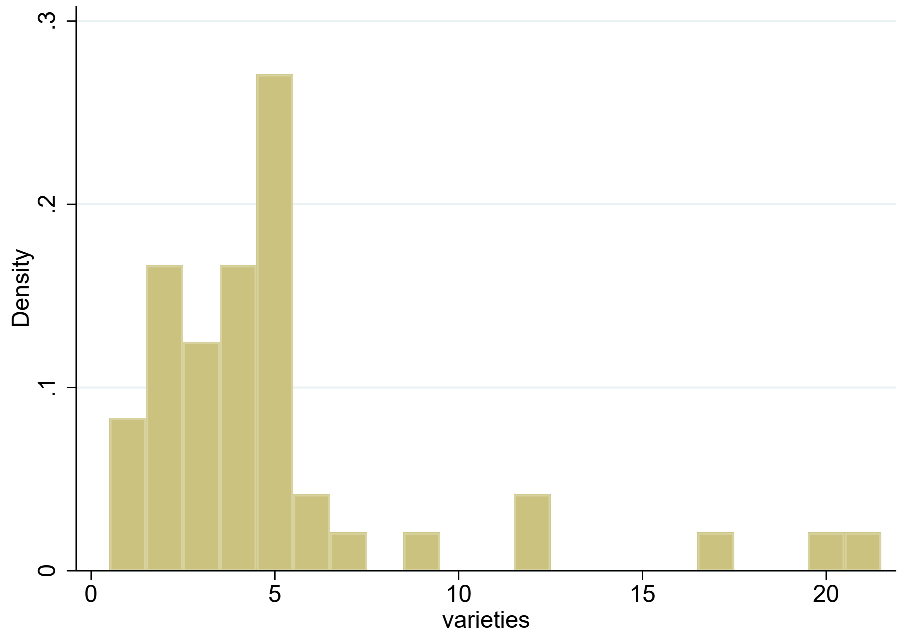

Figure C.1: Frequency distribution of products within commodities (vegetables and fruits)
Notes: The data for pre-lockdown period is used to calculate the number of products of each commodity being sold across cities. The 18 commodities include potato, onion, tomato, banana, apple, spinach/other leafy, brinjal, mango, groundnut, okra, coconut, cauliflower, gourd, cabbage, grapes, beans, citrus fruits and peas. Four commodities - chillies, lemon, ginger and garlic - are excluded from the online availability analyses due to insufficient observations.

Table C.1: Impact of Lockdown on Online Product Availability of Vegetables and Fruits (Heterogeneity by Other Characteristics)

Variable	(1)	(2)	(3)	(4)
X=	Perishability	CPI Weight	POT	High Price
Lockdown	-0.059***	-0.076***	-0.063***	-0.065***
	(0.018)	(0.016)	(0.008)	(0.013)
Lockdown×X	-0.004	0.254	0.002	0.011
	(0.020)	(0.239)	(0.020)	(0.020)
R-sq	0.204	0.204	0.204	0.205
Observations	9800	9800	9800	6560
Mean Availability Pre-Lockdown	0.837	0.837	0.837	0.849
City×Product FE	Y	Y	Y	Y
City×Day of Week FE	Y	Y	Y	Y

Notes: The dependent variable takes a value one if a product is available on a day in a city and zero otherwise. POT refers to potato, onion and tomato. High price refers to a higher than median price (price per kg) in the pre-lockdown period for a product within a given commodity (for vegetables and fruits) and within all the products in the overall category for edible oils, cereals and pulses. Products measured in numbers (e.g number of apples) are dropped due to non-comparability of price with other products leading to a smaller number of products in the last column. The regressions are weighted to give equal representation to each city. Clustered standard errors (at product level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C.2: Effect of Lockdown on Online Prices (Heterogeneity by Initial Listing)

Variable	Veggies & Fruits (1)	Edible Oils (2)	Cereals (3)	Pulses (4)
Lockdown	0.004	0.005	0.027***	0.020**
	(0.004)	(0.005)	(0.005)	(0.008)
Lockdown×High Listing	0.004	-0.022***	-0.007	0.006
	(0.005)	(0.006)	(0.006)	(0.009)
Estimate	0.008	-0.017	0.020	0.026
P-Value	0.031	0.001	0.000	0.000
R-sq	0.972	0.991	0.987	0.969
Observations	7804	4472	14538	7134
City×Product FE	Y	Y	Y	Y
City×Day of Week FE	Y	Y	Y	Y

Notes: The dependent variable is log price of the product. *High Listing* refers to a higher than median percentage days availability in the pre-lockdown period for a product within a given commodity-city pair. A few products having only single products in a city are dropped from the analyses leading to smaller number of observations that the base specification. The regressions are weighted to give equal representation to each city. Clustered standard errors (at product level) in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Notes

1. The price index construction is an ongoing project and is part of the economic activity index initiative at the Indian School of Business. The author, Shekhar Tomar, is one of the members managing this initiative and is working on releasing the index as well as sharing the methodology behind it. Shekhar Tomar also thanks CAFRAL for its help in the collection of data for the initial one-year of the project.

2. The official statistics report commodity-wise index, and we have reconstructed the aggregate official index corresponding to the commodities in our basket.